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Abstract

We test the impact of investor sentiment on a panel of international stock markets. Specifically, we examine the influence of investor sentiment on the probability of stock market crises. We find that investor sentiment increases the probability of occurrence of stock market crises within a one-year horizon. The impact of investor sentiment on stock markets is more pronounced in countries that are culturally more prone to herd-like behavior and overreaction or in countries with low institutional involvement. Results also suggest that investors' sentiment is not a reliable predictor of stock market reversal points.

JEL Classification : G12, G14, G15.

Keywords: Investor sentiment, stock market crises, reversal points.

Introduction

Financial professionals are well aware of the impact of investors' psychology on financial markets. The influence of investors' mood on market movements is regularly discussed in financial periodicals, on the radio and on television. As noted by Daniel Kahneman in a speech entitled "Psychology and Market" at Northwestern University in 2000: *"If you listen to financial analysts on the radio or on TV, you quickly learn that the market has a psychology. Indeed, it has character. It has thoughts, beliefs, moods, and sometimes stormy emotions."* Traditional financial models have difficulty explaining financial crises. The crash of October 1987, for instance, remains enigmatic for researchers. During the crash, stock prices drop an average of 22.6%, a decrease much larger than what can be explained by changes in economic variables (Black, 1988; Fama, 1989; Shiller, 1989; Seyhun, 1990; Siegel, 1992). The view about the market "personality", the market behavioral approach recognizes that investors are not "rational" but "normal" and that systematic biases in their beliefs induce them to trade on non-fundamental information, called "sentiment". Recently, investor sentiment has become the focus of studies on asset pricing.

Several theoretical studies offer models establishing the relationship between investors' sentiment and assets prices (Black, 1986; De Long, Shleifer, Summers and Waldmann, 1990; Barberis, Shleifer and Vishny, 1998; Daniel, Hirshleifer and Subrahmanyam, 2001). Two categories of investors characterize these models: informed traders rationally anticipating asset value and uninformed noise traders who experienced waves of irrational sentiment. Rational traders, who are sentiment free, correctly evaluate assets. Uninformed noise traders' overly optimistic or pessimistic expectations induce strong and persistent mispricing. In these models, informed traders and noise traders compete. Informed traders, the unemotional investors, who force capital market prices to equal the rational present value of expected future cash flows, face non-trivial transactions and implementation costs as well as the

stochastic noise trader sentiment. These elements prevents informed traders from taking fully offsetting positions to correct mispricing induced by noise traders. Hence, to the extent that sentiment influences valuation, taking a position opposite to prevailing market sentiment can be both expensive and risky. Mispricing arises out of the combination of two factors: a change in sentiment on the part of the noise traders, and a limit to arbitrage.

Several empirical studies attempt to measure investor sentiment (Lee, Shleifer and Thaler, 1991; Neal and Wheatley, 1998; Brown and Cliff, 2004). These studies identified direct and indirect sentiment measures. Direct sentiment measures are derived from surveys while indirect measures relied on objective variables that correlate with investor sentiment. Numerous significant publications focus on the impact of sentiment on future stock returns (Solt and Statman, 1998; Brown and Cliff, 2005; Baker and Wurgler, 2006). Finding shows that individual investors are easily swayed by sentiment. Sentiment indicators increases the traditional model explanatory power for stocks that are highly subjective and difficult to arbitrage, e.g small stocks, value stocks, stocks with low prices and stocks with low institutional ownership.

Despite the number of published works on the issue of investor sentiment, several avenues of research remain unexplored. In particular, the empirical question of a relationship between sentiment and stock market crises remains under researched and unresolved. Fluctuations in investor sentiment are often mentioned as a factor that could explain the financial crises but rarely analysed (White, 1990; De Long and Shleifer, 1991; Shiller, 2000). Most previous studies test the ability of sentiment indicators to predict stock prices in aggregate or in period of normal market conditions. Few studies have attempted to directly link sentiment indicators to market crises. Only two studies were identified and those were limited to the U.S. stock market crash of 1987 (Siegel 1992 and Baur, Quintero and Stevens, 1996).

Our goal, therefore, is to study the ability of sentiment indicators to predict international stock market crises. To achieve our objective, we built a "leading indicator" of crises using data from 16 countries. By means of a logit model, we related our qualitative crises indicator to a set of quantitative macro-economic variables and the indicator of sentiment. Specifically, we tested whether consumer confidence - as a direct proxy for individual investor sentiment- influenced the probability of stock market crises in 16 countries. Results confirmed the significant impact of investors' sentiment on financial crises. The impact of sentiment is more pronounced for countries that are culturally more prone to herd-like behavior and overreaction and countries with low institutional development.

Our study diverges from previous research in several ways. First, we use investors' sentiment as an indicator of financial crises. A better grasp of stock market crises should deepen our understanding of the dynamic process of stock price adjustments to intrinsic value. Second, our sample of different countries allows comparisons with U.S. data. Furthermore, the use of panel data is known to generate more accurate predictions for individual outcomes by pooling the data (Ang and Bekaert, 2007). Third, taking an international perspective allows us to analyse the cross-country variation in the sentiment-return relationship. A cross-country study can provide evidence on how cultural differences as well as institutional differences affect the sentiment-return relation. Finally, focusing on stock market crises allows us to examine the concept of price reversal, another under researched phenomenon.

The remainder of this article is organized as follows. The second section is devoted to a summary of the literature. The third section presents the methodology and variables used to explain the probability of a stock market crisis. The fourth section analyzes the empirical results obtained. The fifth section investigates cross-country results. In the sixth section, results from the test conducted on price reversal are presented. The seventh section concludes the study.

2. Literature Review

The relationship between the variables sentiment and stock returns is at odds with classic finance theory which states that stock prices mirror the discounted value of expected cash-flows and that irrationalities among market participants are removed by arbitrageurs. Behavioral finance, on the other hand, suggests that optimistic and/or pessimistic investors' expectations affect asset prices. Baker and Wurgler (2006) pointed out that sentiment-based mispricing is based on an uninformed demand of some investors, the noise traders, and a limit to arbitrage. Since it is unknown how long buying or selling pressures from overly optimistic or pessimistic noise traders will persist, mispricing can be persistent. However, every mispricing must eventually be corrected so one should observe that high levels of investor optimism are followed by low returns and vice versa.

Validation for behavioral finance started with studies examining the correlation between macro-economic variables and stock prices. The process by which security prices adjust to the release of new information has also been studied extensively. Results of these studies show that stock prices reflect more than fundamental variables. As early as 1971, Niederhoffer highlights the weak stock market reaction to events considered important (Election, War, Change of foreign leadership..., etc,) while very strong asset price variations remain difficult to explain. More recently, Cutler, Poterba and Summers (1991) examined stock price changes in relation to the arrival of information about macro-economic performance. They established that macro-economic variables explained approximately a third of the variance in stock returns. They also showed that information, such as news about wars, the presidency, or significant changes in financial policies explain some but not all of the variance in stock returns. These findings are similar to those reported by Shiller (2000) who established that volatility of market prices are well above what is predicted by changes in economic indicators.

Stock price volatility during crashes defies the explanatory power of the traditional financial models. The conventional models, in which unemotional investors force capital market prices to equal the rational present value of expected future cash flows, have considerable difficulty explaining stock price volatility. Researchers in finance have therefore been working to supplement these traditional models. Shiller (1987) surveyed both individual and institutional investors inquiring about their behavior during the 1987 crash. He showed that most investors interpreted the crash as the outcome of other investors' psychology rather than fundamental financial variables such as earnings or interest rates. Siegel (1992) confirmed that changes in corporate profits and interest rates were unable to explain the rise and subsequent collapse of stock prices in 1987. He suggested that a shift in investor sentiment was a factor in the stock market's deep decline¹. During his speech on December 5, 1996 at the American Enterprise Institute, Greenspan delivered his memorable line that "...irrational exuberance has unduly escalated asset values...". Greenspan's warning, unfortunately, did not prevent the swelling and bursting of the tech bubble in 2000.

The events of 1987 and 2000 have led several well renowned financial economists to distance themselves from the traditional finance theory (Black, 1986; Shiller 1989; Thaler, 1999; Rubinstein, 2001; Shefrin, 2005). Most financial economists recognized that the market has mood swings and considered behavioral finance as an alternative. The link between asset valuation and investor sentiment became the subject of considerable deliberation among financial economists. A vast number of empirical investigations with different measures of investor sentiment have been conducted. While theoretical models have incorporated the existence of noise traders into equilibrium asset pricing early, empirical evidence on the correct proxy for sentiment or on the significance of investor sentiment does not provide clear findings.

¹ Contrary to this finding, Baur, Quintero and Stevens (1996) reported that during the periods that surrounded the crash, only changes in fundamentals have a statistically significant impact on the movement of stock prices.

Neal and Wheatley (1998) examined the forecast power of three popular measures of individual investor sentiment: the level of discounts on closed-end funds, the ratio of odd-lot sales to purchases and the net mutual fund redemptions. They found that net fund redemptions predict the size premium and the difference between small and large firm returns. They also reported a positive relationship between discounts and small firm's expected returns but no relationship between discount and large firm's expected returns. These results are consistent with the investor sentiment hypothesis that small firms stocks are held primarily by small investors. Brown and Cliff (2004) scrutinize various direct and indirect sentiment indicators. They report that direct (surveys) and indirect measures of sentiment are correlated. Although indicators of sentiment strongly correlated with contemporaneous market returns, they show that sentiment has little predictive power for near-term future stock returns. Qiu and Welch (2006) reported that surveys measuring investors' sentiment are related to other popular measures of investors' sentiment and to recent stock market returns. They also showed that although indirect measures circumvent the lack of sample size and statistical representativeness of the direct measurements, the theoretical link to investor sentiment is weaker than with the direct indicators.

Other indirect indicators using statistical series from futures trading activities can also be found in the literature. Simon and Wiggins (2001) measured sentiment using the put-call ratio and found that the sentiment indicators are statistically and economically useful contrarian indicators in the S&P 500 futures market. Schmitz, Glaser, and Weber (2005) identified warrant trades as an effective measure of sentiment. Lee and Song (2003) measured noise investors' sentiment with the equity put-call ratio and the market volatility (VIX) index. Their findings provided insights into the relationship between trading volume and volatility by considering the changing sentiments of different traders. Baker and Wurgler (2006) constructed an index of investor sentiment as the first principal component of six indirect

investor measures suggested in the literature (trading volume as measured by NYSE turnover; the dividend premium; the closed-end fund discount; the number and first-day returns on IPOs; the equity share in new issue). They found that the sentiment effects are stronger among stocks whose valuations are highly subjective and difficult to arbitrage.

Much work has been aimed at studying the impact of direct measures on the stock returns. However, the results of these investigations have also been mixed. Solt and Statman (1988) and Clarke and Statman (1998) find that the sentiment indicator published by Investors Intelligence is useless as an indicator of future stock price changes. Fisher and Statman (2000) studied the sentiments of three groups of investors: small investors, newsletter writers, and Wall Street strategists, and found that the sentiments of both small investors and Wall Street strategists were reliable contrary indicators for future S&P 500 stock returns, but no statistically significant relation between the sentiment of newsletter writers and stock returns was uncovered. Using survey data on investor sentiment, Brown and Cliff (2005) provided evidence that sentiment affects asset valuation. The authors show that excessive optimism leads to periods of market overvaluation and high current sentiment is followed by low cumulative long-run return.

Other studies focusing on indexes of consumer confidence analyzed the impact of sentiment on the stock market. Otoo (1999) reported a strong contemporaneous relationship between changes in the consumer confidence index and the stock returns. Examining the causal relationship among the variables, she stated that returns Granger-cause consumer confidence at very short horizons but not vice versa. Fisher and Statman (2003) found statistically significant relationships between some components of consumer confidence and subsequent NASDAQ and small cap returns. Charoenrook (2006) examined whether sentiment, as measured by yearly change in the University of Michigan Consumer Sentiment Index, has affected stock returns. The author found that changes in the index reliably

predicted excess stock market returns. Lemmon and Portniaguina (2006) also reported evidence that investors appear to overvalue small stocks relative to large stocks during periods when consumer confidence is high and, vice versa. Moreover, Schmeling (2009) examined whether consumer confidence affects expected stock returns in 18 industrialized countries. In line with recent evidence for the U.S, he found that sentiment negatively forecasts aggregate stock market returns on average across countries. This relation also holds for returns of value stocks, growth stocks, small stocks, and for different forecasting horizons. Similarly, Baker, Wurgler and Yuan (2009) constructed indexes of investor sentiment for six major stock markets and decomposed them into one global and six local indices. They determined that sentiment, both global and local, is a statistically and economically significant contrarian predictor of market returns, particularly for highly subjective and difficult to arbitrage stocks. This extends prior US evidence to international markets.

The prior literature review highlights the lack of consensus about the best measure of sentiment or on whether sentiment in fact affects stock prices. While existing studies test the impact of sentiment on individual stocks and portfolios of stocks whose valuations are highly subjective and difficult to arbitrage, this paper takes a different approach. We propose to test the impact of investor sentiment on international capital markets by studying its ability to predict stock market crises. A priori, stock market crises should be preceded by periods of rising investor euphoria. Therefore, we expect that periods characterized by excessive investors' optimism are followed by stock market crises.

3. The stock market crises and the role of investor sentiment

As mentioned above, our goal is to test the ability of investor sentiment to predict international stock market crises. The study includes 15 European countries and the United States. Data includes monthly observations for the period between April 1995 and June 2009. Economic data availability dictated the beginning time period for most countries. As

discussed below, our study includes financial and macro-economic variables and survey results. The list of the countries and the data sources used are presented respectively in appendix 1 and table 1.

[INSERT TABLE 1]

3.1. Identification of stock market crises

Most studies define equity crises as an abrupt and rapid drop in the overall market index. The change of the index can be the predecessor of larger decreases, higher dispersions of probable losses and/or more uncertainty about the return of firms. The first step of our study consists of identifying the financial crises that have occurred during the period considered in the regions studied. To achieve this goal, we use the methodology proposed by Patel and Sarkar (1998) which is, according to these authors, widely used by practitioners.

In their study, Patel and Sarkar (1998) designed a crises indicator called CMAX. The CMAX compares the current value of an index with its maximum value over the previous T periods, usually 1 to 2 years. The CMAX ratio is calculated by dividing the current price by the maximum price over the previous two year period.

$$CMAX_{i,t} = \frac{P_{i,t}}{\max(P_{i,t-24}, \dots, P_{i,t})}$$

Where P_{it} is the stock market index at time t for country i. The rolling maximum in the denominator was defined over a relatively short period (24 months) to avoid losing too many data points.

Boucher (2004) describes the CMAX as an indicator of the decline in volatility. This indicator equals 1 if prices rise over the period considered, indicating a bullish market. The more prices fall, the closer the CMAX gets to 0. A crisis is detected whenever CMAX exceeds a threshold set at the mean of CMAX minus two standard deviations. To avoid

counting the same crisis more than once, a crisis is automatically eliminated if detected twice over a twelve month period.

The stock market crises indicator for country i at time t , $C_{i,t}$, is defined as follow:

$$C_{i,t} = 1 \text{ if } CMAX_{i,t} < \overline{CMAX_i} - 2\sigma_i$$

$$C_{i,t} = 0, \text{ otherwise}$$

Given the indicator structure, share price decreases are already well in progress when a crisis is identified, i.e. $C_{i,t}$ uncovers abnormal drops in prices rather than the market turning point. This indicator only identifies as crises those events that eliminate the previous two years of gains.

Similarly to Patel and Sarkar (1998), we define the following concepts : (i) the beginning of a crises as the month when the index reaches its historical maximum over the 2-year window prior to the month when the crash is triggered, (ii) the beginning of the crash corresponds to the month when the CMAX intersects with a threshold, (iii) the date of trough is the month when the price index reaches its minimum, (iv) the date of recovery is the first month after the crash when the index reaches the pre-crash maximum, (v) the magnitude of the crises is the difference between the value of the index at its maximum and at its minimum, (vi) the length of the trough is the number of months between the date of the beginning of the crises and the date of the trough, and (vii) the length of the recovery period is the number of months for the index to return to the maximum.

Figure 1 illustrates these concepts on the US stock market. As shown, three crises are identified during the period 1995-2009. The first crash occurred in July 2001 and reached a trough eleven months later in June 2002. It was characterized by a decrease of 40% in the S&P500 and the crisis ended 81 months later, in April 2007. The second crash took place in August 2002. It took 52 months for the market to regain the 43% loss during the crisis. The third crash is identified in June 2008 and the magnitude of the crises is 52.55 %.

Figure 1 : US equity market index

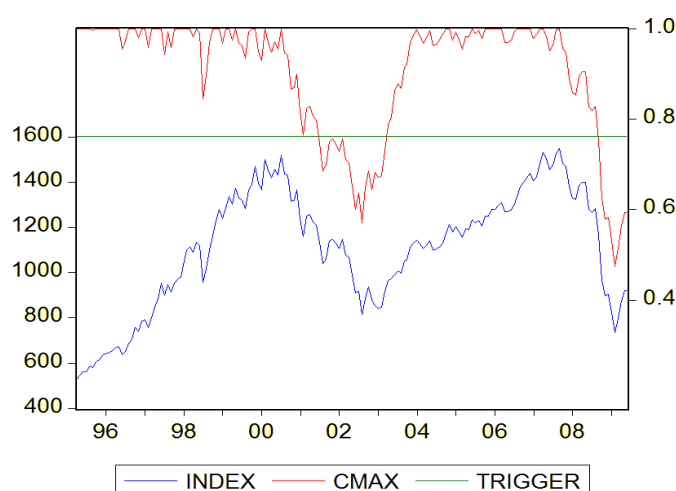


Table 2 presents the characteristics of the crises identified in our sample. During the period analyzed, we detect 44 crises, i.e. an average of 2.75 per country. Consistent with Roll (1988) who found substantial price increases in many international stock markets in the nine months prior to the October 1987 stock crash, the average returns before the crises are high. In our sample, the pre-crises annual median returns are equal to 86.38%. Further, most of the crises identified correspond to well known historical events, such as the internet bubble of the 2000's and the recent subprime crisis.

[INSERT TABLE 2]

3.2. The methodology used to link investor sentiment to stock market crises

The seventies saw the emergence of the first models for forecasting crises including banking crises and currency crises (Early Warning Models or Early Warning Signals). Most of these models used discriminant analysis and logit/probit models. Discriminant analysis is a method used to find linear combinations of features which best separate two or more classes of objects or events, in this case, healthy countries from those facing difficulties. Discriminant analysis is not designed to determine the causes of crises. Logit/probit models², on the other hand, help to isolate "leading indicators" of financial crises. The idea underlying

² For a detailed discussion of logit models, see Maddala (1983).

these models is to identify economic variables having a specific behavior before the onset of the crises and to estimate the probability of occurrence of these crises during a specific period (usually one or two years), taking into account the information these variables included (Frankel et Rose, 1996; Demirguc-Kunt et Detragiache, 2000; Bussiere et Fratzscher, 2006; Lau et Yan, 2005). Our approach, outlined below, is inspired by the logit/probit models.

▪ **The dependent variable**

The logit approach has the advantage of providing a framework for statistically measuring the magnitude and significance of the effects of various explanatory variables on the onset of a financial crisis. It explains the occurrence or the non-occurrence of a crisis with a binary variable and explanatory variables found in the real sector of the economy, i.e. financial variables, external sector and fiscal variables.

The logit model of the occurrence of a crisis with lagged values of early warning indicators as explanatory variables requires the construction of a crisis dummy variable that serves as the endogenous variable in the regression. To construct our dependent variable, we closely follow the methodology of Brussiere and Fratzcher (2006). Using the crises defined above, we define a dummy variable $I_{i,t}$. $I_{i,t}$ equals to 1 during the crisis and the twelve months preceding it and 0 during calm time periods. The 11 months following the crisis are excluded, as the post-crisis period is irrelevant for the estimation and may even distort the quality of the model if it is aggregated with calm periods.

$$\begin{aligned} I_{i,t} &= 1 \text{ if } \exists k \in \{1, \dots, 12\} \text{ such as } C_{i,t+k} = 1 \\ I_{i,t} &= n.a \text{ si } \exists k \in \{1, \dots, 11\} \text{ such as } C_{i,t-k} = 1 \\ I_{i,t} &= 0, \text{ otherwise} \end{aligned}$$

- **The independent variables**

The following sub-sections present the variables proposed to explain the crises detected in the sample. The first sub-section introduces “traditional” variables. The second sub-section focuses on the variable sentiment.

- **The traditional variables**

Contrary to banking and currencies crises where studies are abundant, very few studies have been published about the variables explaining the stock market crises. For the period 1929 – 2000, the literature indentified two groups of variables³.

The first group of explanatory variables reflects the price acceleration and the divergence between asset prices and their intrinsic value. The variables are the year-on-year change in stock prices (RET) and the price earnings ratios (PER).

The RET is a good substitute for price acceleration and decline. Indeed, the returns tend to decline gradually before the onset of the crisis. The PER is widely used to express a firm's market valuation relative to its fundamental value. Campbell and Shiller (2001) showed that when stock market valuation ratios are at extreme levels by historical standards, some weight should be given to the mean-reversion theory that prices will fall in the future to bring the ratios back to more normal historical levels. Indeed, If we accept the premise for the moment that valuation ratios will continue to fluctuate within their historical ranges in the future, and neither move permanently outside nor get stuck at one extreme of their historical ranges, then when a valuation ratio is at an extreme level either the numerator or the denominator of the ratio must move in a direction that restores the ratio to a more normal level.

The second group of variables includes monetary aggregates and an indicator of financial instability. In this category, we retain inflation rate (INF), real interest rate (INT) and ratio domestic credit/GDP (CREDIT).

³ These variables are similar to those proposed by Boucher (2004) and Goudret and Gex (2008).

Stock prices are negatively correlated to inflation and financial crises are characterized by high volatility of inflation (Nelson, 1976; Fama et Schwert, 1977; Blanchard, 1993). For example, Fama and Schwert (1977) established that most stock markets have the tendency to perform poorly when inflation is high. Using US data since 1789, Bordo and Wheelock (1998) showed that most financial crises occurred during periods with high variation in inflation. The interest rates are also often cited as a good indicator of financial crises. Interest rates tend to decline significantly before the collapse of the stock markets. Finally, Domestic credit, another independent variable, is used to capture financial instability often visible before financial crises. As documented in Corsetti, Pesenti and Roubini (1998), Goldstein (1998) and Kamin (1999), when domestic credit grows at a fastest rate than GDP, this can lead to excessive risk-taking from investors with large losses on loans in the future. With rapid growth of lending, banking institutions might not be able to add the necessary managerial capital (well-trained loan officers, risk-assessment systems, etc.) fast enough to enable these institutions to screen and monitor these new loans appropriately. The outcome of the lending boom leads to the deterioration in bank balance sheets, leading economies into financial crises.

- **The behavioral variable**

A universally accepted measure of investor sentiment has not yet been identified. The financial literature proposes two categories of proxies for investor sentiment, direct and indirect indicators. Direct sentiment measures are based on polling market participants through surveys. Indirect measures are made up of a time series of macro-economic and financial variables, used to proxy the unobserved sentiment factor⁴.

For this study, we favored the consumer confidence index⁵. This variable seizes some of the crises aspects not already contained in macro-economic indicators. The use of the

⁴ See, for instance, Brown and Cliff (2004) for a detailed discussion of sentiment measures.

⁵ Details of consumer confidence survey are given in Appendix 2.

consumer confidence index appeared logical. First, data on the consumer confidence index is available for the majority of developed countries since the mid-80s. Second, because most countries use similar surveys to gather data, comparisons across countries are possible⁶.

Notice that we are not alone; among the various direct indicators, the consumer confidence index seems to be the preferred indicator of the majority of researchers. Otoo (1999), Fisher and Statman (2003), Qiu and Welch (2006) and Lemmon and Portniaguina (2006) presented several additional arguments in support of this variable:

- Although consumers polled for the University of Michigan Consumer Confidence Index are not asked directly for their views on security prices, changes in the Consumer Confidence Index correlate very highly with changes in stock prices.
- Participation of individual households in financial markets has increased substantially over recent years suggesting that measures of consumer confidence may be a useful barometer of how individual investors feel about the economy and the financial markets
- Researchers utilize longitudinal data which allows for more robust and significant studies. Direct measures of sentiment derived from surveys circumvent some of the drawbacks of indirect measures⁷.
- Because the consumer confidence index captures individual beliefs, it reflects the philosophy of behavioral finance; including the opinions of imperfect people who have social, cognitive, and emotional biases (Shleifer, 2000).

Finally, as many researchers⁸ emphasize that the direct indicator of sentiment reflects an economic component and a psychological aspect, we decompose the consumer confidence index into a component related to the business cycle, i.e. macroeconomic “fundamentals” and

⁶ The European questionnaires have been harmonized since the mid-80s. Michigan consumer confidence survey covers 5 years. The European survey covers 1 year and has an average number of participants of 3000 respondents.

⁷ Because indirect measures are made up of time series of macro-economic and financial variables, they may not exclusively represent investors' sentiment.

⁸ See Brown and Cliff (2005), Lemmon and Portniaguina (2006), Kumar and Lee (2006) and Baker and Wurgler (2006).

a residual component that we interpret as a purer measure of “sentiment” ($SENT^\perp$). Specifically, we treat the residual from the following regression as our measure of sentiment unwarranted by fundamentals⁹.

$$SENT_{i,t}^\perp = \alpha + \beta_j \sum_{j=1}^J FUND_{i,t}^j + \varepsilon_{i,t}$$

The variables that capture the component related to the business cycle, i.e. macroeconomic “fundamentals” ($FUND$) are: (i) the changes of the industrial production (IP), (ii) the growth in consumption of durables (CD), non-durables (CND) and services (CS), (iii) the spread defined as the difference in yield between the 10-year and 3-month government bonds (ST) and (iv) the dividend yield measured as the dividend divided by the market capitalization (DY). We believe that these variables are as comprehensive as those commonly used in the literature. This procedure reduces the likelihood that variation in sentiment is related to systematic macroeconomic risks. The sentiment measure is orthogonalized with respect to several contemporaneous variables.

▪ The model used

The dependent variable $I_{i,t}$ is explained by the macro-economic indicators and the variable sentiment via a logit model, i.e. we explained our crises indicator ($I_{i,t}$) with a set of quantitative macro-economic variables and the indicator of sentiment. In seeking to estimate the probability that the variable $I_{i,t}$ is equal to 1, we estimate the probability of a crisis within a 1 year window. In other terms, the model attempts to predict whether a crisis will occur during the coming 12 months.

Specially, we successively estimate three different logit models. Model 1 includes only macro-economic variables. Model 2 focuses on sentiment. Model 3 combines macro-economic and sentiment variables¹⁰.

⁹ Due to lack of space, we are not reporting all the regression results. Detailed results are available upon request.

¹⁰ The explanatory variables have been standardized to insure comparability for all countries.

$$\Pr(I_{i,t} = 1) = f(\alpha + \sum_{k=1}^n \alpha_k X_{i,t}^k) \quad (1)$$

$$\Pr(I_{i,t} = 1) = f(\alpha_0 + \alpha_{n+1} SENT_{i,t}^\perp) \quad (2)$$

$$\Pr(I_{i,t} = 1) = f(\alpha' + \sum_{k=1}^n \alpha_k X_{i,t}^k + \alpha_{n+1} SENT_{i,t}^\perp) \quad (3)$$

In the equations above, $I_{i,t}$ is the crisis indicator variable defined above, X^k the matrix of explanatory variables, α_k the vector of coefficient estimates and f a logistical function of the

type : $f(z) = \frac{e^z}{1 + e^z}$.

3.3. The model forecasting ability

To evaluate the performance of the model, we use the signals approach (Kaminsky, Lizondo and Reinhart, 1998; Demirguc-Kunt and Detragiache, 2000; Bussiere and Fratzscher, 2006). The method compares the probability of a crisis generated by the model, the models predicted probability, with the actual occurrence of a crisis. As the predicted probability is a continuous variable, we must decide on a cut-off or threshold probability above which the predicted probability can be interpreted as sending a signal of a pending crisis. The model performs well if the predicted probability corresponds to a crisis as identified in our sample. As shown in the table 3, four situations are possible:

Table 3: Evaluating the performance logit model

		Model logit	
		Signal was issued	No signal was issued
Actual crisis	The indicator forecasts a crisis $I_{it}=1$	Crisis properly planned	Signal Missing (Error A)
	The indicator does not forecast a crisis $I_{it}=0$	False alarm (Error B)	No crisis properly planned by the signal

Table 3 shows two kinds of errors. In the case of type A errors, the model does not detect actual crises while the type B errors incorrectly identifies crises that do not occur. A perfect

indicator would only produce observations that belong to the north-west (NW) and south-east (SE) cells of this matrix, minimizing the type A and type B errors.

The performance of logit model depends largely on these two types of errors. The main question is the optimal threshold level. The lower the threshold, the more signals the model will send with the drawback of having numerous false signals. By contrast, raising the threshold will reduce the number of false signals at the expense of an increase in the number of missed crises signals. Notice, however that the costs associated with the two types of errors are not the same. Type A errors, missing a crisis that ended up materializing, are larger than type B errors consisting of incorrectly anticipating a crisis that will not occur. As suggested by Berg and Patillo (1998), Boucher (2004) and Coudert and Gex (2008), we decided to present the results for alert thresholds set at 25% and 50%.

4. Regression results

Our goal is to estimate the incremental predictive power of the sentiment variable compared to other variables habitually used in the literature. The findings are presented in three parts. Part 1 shows the results of a model including the fundamental economic and financial variables. Part 2 focuses on the sentiment variable. Part 3 combines economic, financial and sentiment indicators. Table 4 presents the results.

[INSERT TABLE 4]

4.1. The predictive power of the traditional variables

With the exception of the INF variable, all macro-economic variables included in Model 1 are significant and display the expected sign. The model is performing well, the maximum likelihood confirms the quality of the overall fit of the model and the hypothesis of joint nullity of all the regression coefficients except the constant can be rejected.

These findings add credibility to PER, RET, INT and CREDIT as predictors of financial crises. Bubbles are often characterized by an unsustainable increase in asset prices.

Traditionally, the PER is used to give an idea of what the market is willing to pay for the company's earnings. A stock with a high PER is often interpreted as an overpriced stock while a stock with low PER may indicate a "vote of no confidence." Our study shows that an increase in the PER is positively correlated with the probability of a financial crisis. This result supports the mean-reversion theory that when prices are high they will fall, bringing the PER back to normal historical levels.

The variable INT negatively impacts the probability of a financial crisis. This result explains why monetary authorities cut rates to stabilize the economy and limit the adverse consequences of bursting bubbles. The sign is also negative for returns (RET), which already tend to decline at the onset of the crisis. As far as the variable CREDIT is concerned, a positive and significant coefficient supports previously reported studies that financial aggregates, such as domestic credit, are early indicators of financial crises. Rapid credit growth has been associated with macroeconomic and financial crises, originating from macroeconomic imbalances and banking sector distress. This is why policymakers face the dilemma of how to minimize the risks of financial crisis while still allowing bank lending to contribute to higher growth and efficiency.

Contrary to our expectations, the variable INF is negatively correlated to the probability of a financial crisis. A significant negative coefficient is intuitively difficult to comprehend as it implies that policymakers' commitment to price stability increases the probability of a crisis. A negative correlation, can however, be explained by the "paradox of credibility". Goodfriend (2001) and Borio and Lowe (2002) showed that when inflation is under control, tensions of productivity cannot be detected by inflation numbers but rather by instability in the financial sector¹¹. The idea has been shared by the BIS economists, who have been

¹¹ The bursting of the technology bubble in the beginning of the years 2000 and the recent subprime crises took place at the bottom of a relatively stable period.

arguing along these lines for years, finding more sympathetic ears among central bankers than among academics.

McFadden R^2 statistic is 40.1%, suggesting the quality of the regression. The results also show that the percentage of crises correctly predicted stock market is high. Types A errors are low showing that the model predicts correctly 64% (threshold 50%) and 70% (threshold 25%) of the crises. Note also that Types B errors (false alarms) are relatively low for the two thresholds (15.21% when the threshold is 50% and 21.67% when the threshold is 25%).

4.2. The predictive power of the variable sentiment

Results from the second model tend to confirm our hypothesis about the variable $SENT^L$. The variable is statistically significant and it shows the expected positive sign. The model predicts correctly 47% and 68% of the crises at threshold of 50% and 25% and the percentages of Type B errors are low (13.27% when the threshold is 50% and 16.21% when the threshold is 25%).

This result corroborates one of the fundamental hypotheses of behavioral finance that there is a negative relationship between investor's sentiment and the future performance of stocks (Lee, Shleifer et Thaler, 1991; Neal et Wheatley, 1998; Glushkov, 2006; Schmeling, 2009). When investor sentiment is low, subsequent returns are relatively high. On the other hand, when sentiment is high, the pattern is reversed; stocks are overpriced and will experience a decline in value. Stocks market bubbles coincide with periods of overly optimistic investors. However, every mispricing must eventually be corrected so excessive optimism (overvaluation of the market) will inevitably be followed by sharp drops in stock prices (stock market crises).

4.3. The incremental predictive power of the variable sentiment

Results of the third model show that the variable $SENT^+$ remains significant even after controlling for the financial and economic variables. Results also indicate that with the exception of PER, all fundamental variables remain significant and keep their expected signs.

These findings suggest that the use a variable sentiment rather than the traditional PER improves our ability to predict stock prices departure from their fundamental values. Indeed, when the sentiment indicator is introduced in the model, the price-earnings ratio losses its explanatory power. This is a significant result as the price-earnings ratio is always the focus of management. This result should be pleasing to financial analysts who often complain that the PER multiples are unsophisticated discount factors failing to account for, among many factors, interest rates and/or inflation rates over the forecast periods.

The model displays good results. The introduction of variable SENT improves the statistical quality of the model, the McFadden R^2 gains about 6.1% when compared to the first model. The model also predicts correctly 72% and 81% of the crises at thresholds of 50% and 25%. Adding a sentiment indicator, in addition to macroeconomic variables, improve the model prediction of the stock market crises¹².

4.4. Out-of-sample performance of logit model

If a relatively low percentage of errors is necessary to establish the quality of the model, it is not sufficient to conclude that the model is efficient (Berg and Pattillo, 1999). Thus, it is necessary to determine its relevance from out-of-sample observations to judge the validity of the logit model. The logit model should be estimated over a given period, then simulated out-of-sample. To test whether our model is able to predict crises out-of-sample, we estimate the

¹² One potential drawback of the logit model with pooled data is that it ignores the cross-section and time series dimensions of the data. For example, the legal system or the political situation of a country could be such that we permanently understate the probability of a stock market crisis (see Brussi re and Fratzcher, 2006, p.960). To check the robustness of our results, we estimate panel logit model with fixed and random effects. The results obtained are virtually the same. This suggests that ignoring country-specific information does not constitute a bias in our estimation. Results are available upon request.

model on April 1995-December 2007 and compute the probability of a crisis in the following 12 months. The goal is to test the accuracy of predictions on out-of-sample data, i.e., the crisis at the end of our sample (the subprime crisis in 2008).

We find that the model is performing well, even out-of-sample, predicting most of the subprime crises occurring during the year 2008. The model failed to predict only the crisis of Denmark in September 2008, the predicted probability of a stock market crisis in Denmark is equal to 0.198¹³. Overall, the out-of-sample performance of our model is so robust and would have allowed the correct anticipation of the most recent subprime crisis.

5. Cross-country analyses

We examine whether our results are sensitive to the countries been allocated in two groups depending on some determinants of market integrity and herd-like overreaction. Specifically, we use our cross-section of countries to determine if there is evidence that the impact of sentiment on stock market crises is higher for countries with less market integrity and for countries culturally prone to overreaction-like behavior and herd behavior.

Market integrity means that financial markets with higher level of institutional sophistication are characterized by a better flow of information and are consequently more efficient. The market integrity variables retained in our study can be found in La Porta, Lopez-de-Silanes, Shleifer and Vishny (1998), Chui, Titman and Wei (2008) and Schmeling (2009). These variables include (i) the index of anti-director rights, (ii) the corruption perception index and (iii) the accounting standards index¹⁴.

The variables used to assess herd-like overreaction are rooted in the article of Hofstede (2001). The first index measures the level of individualism of a country and the second one, the so-called uncertainty avoidance index, measures individual's attitude toward new and

¹³ For Denmark, the out-of-sample predicted probability of a crisis in the following 12 months is below the 25% threshold. Detailed results are available upon request.

¹⁴ In order to make results easier to interpret, we have rescaled all market integrity indicators. Higher value indicates higher market integrity.

unexpected occurrences. According to Hofstede (2001), individualism affects the degree to which people display an independent behavior rather than a dependent behavior. The author argued that children in collectivistic cultures build their identity from their social system. He showed that higher levels of collectivism indicate a tendency towards herd like behavior. The uncertainty avoidance index measures the degree to which a culture programs its members to react to new and unusual situations. Hofstede (2001) documented that people in countries with high uncertainty avoiding levels react in a more emotional way compared to countries with low levels of uncertainty avoidance. Therefore we use the uncertainty avoidance as a proxy of the tendency of individuals to overreact. Hofstede (2001) showed that the uncertainty avoidance index is correlated with the collectivism index since the uncertainty avoidance index captures cross-country differences in the propensity of people to follow the same sets of rules and thus to behave in the same manner. Therefore, higher levels of the uncertainty avoidance behavior should indicate a tendency towards more herd-like behavior. Findings are depicted in Table 5.

[INSERT TABLE 5]

For both groups of countries, the McFadden R^2 is higher when sentiment is added in the model. However, results show that the variable $SENT^{\perp}$ is only significant for the group of countries showing high herd-like behavior and low market integrity. For the other group, $SENT^{\perp}$ is significant when the index uncertainty avoidance is used. Furthermore, the model quality is good. We find that the errors of types A and B are lower for collectivistic countries, countries with high uncertainty avoiding index and countries with low institutional involvement.

Findings show that using the variable sentiment improves our ability to predict stock prices departure from their fundamental values in countries where herd-like behavior and overreaction behavior are strong and where market integrity is low. The evidence in the table

indicates that culture has a different effect on stock market crises, a result consistent with the idea that investors in different cultures have different biases.

6. Investor sentiment as a predictor of reversals market points

Results so far indicate that the introduction of a sentiment indicator improves our forecast of stock market crises. From the viewpoint of the investor, however, it is more important to identify the turning point of the market than the moment when falling prices have reached an abnormally low level.

Contrary to previous studies on investors' sentiment, our methodology can be adjusted to study the market reversals points. Specifically, we use the dates of peaks previously determined to detect the turning points of the stock markets. As with the prediction of stock market crises, we construct a binary indicator $PR_{i,t}$ ¹⁵. The indicator takes the value of 1 for the month corresponding to the top of the index and the twelve months before the top and 0 otherwise. The 11 months following the peak are excluded from the sample. Our model is now adapted to identify these stock market reversals points. Table 5 summarizes findings.

[INSERT TABLE 6]

Sentiment indicator is positively correlated with the probability that asset prices reach their highest level within a one-year horizon. In other words, when our model includes a sentiment indicator it predicts the potential of triggering a stock market crisis in the next 12 with more accuracy than when only traditional financial and macroeconomic indicators are used. Financial crises are often preceded by excess optimism leading to value securities above their fundamental values. The euphoria of investors drives up stock prices leading to financial crises within a one-year horizon.

¹⁵ We use the model of Coudert and Gex (2008).

The introduction of variable sentiment improves the prediction of turning points both in terms of quality of regression or quality forecasting. Notice however that these results must be interpreted with caution. Indeed, the percentages of errors of types A and B are relatively large and the McFadden R^2 does not exceed 14.2%. Thus, predicting stock market reversals provides weaker performance than forecasting crises.

Conclusion

The general finding of a sentiment-return relation is at odds with standard finance theory which predicts that stock prices reflect the discounted value of expected cash-flows and that irrationalities among market participants are erased by arbitrageurs. In contrast, the behavioral approach suggests that waves of irrational sentiment, i.e. times of overly optimistic or pessimistic expectations, can persist and affect asset prices for significant periods of time, eventually generating crises. This paper attempts to assess the relationship between investor sentiment and stock market crises.

Specifically, our paper empirically examines the influence of investor sentiment on the probability of occurrence of stock market crises over the period 1995-2009. We use panel data of 15 European countries and the United States to estimate a multivariate logit model. It appears that the sentiment of investors positively influence the probability of occurrence of stock market crises within a one-year horizon. Furthermore, the investor sentiment provides an incremental predictive power compared to other variables routinely used in the literature. The impact of investor sentiment on stock markets is stronger for countries that culturally more prone to herd-like behavior and overreaction and countries with low efficient regulatory institutions. This result is important for portfolio managers; investors' sentiment is a good predictor of securities overvaluation. Finally, this is a key result for financial market regulators, investors' sentiment can be useful to anticipate stock market crisis.

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Annexe 1

The data stock market indices, mainly drawn from the Datastream database for the period 1995-2008, are the following : BEL 20 (Belgium), PRAGUE PX 50 (Czech Republic), OMX Copenhagen (Denmark), DAX 30 (Germany), HE GENERAL IRELAND (Ireland), ATHENS SE GENERAL (Greece), IBEX 35 (Spain) , CAC 40 (France), 30 MILAN COMIT (Italy), ESTONIA TALS INDEX (Estonia), PORTUGAL PSI-20 (Portugal), SLOVENIAN EXCH. STOCK (Slovenia), DJWI FINLAND (Finland), SWEDEN OMX (Sweden), FTSE 100 (UK) and the S&P 500 Composite (U.S.). The PER and dividend yield on stock indices are extracted from Bloomberg.

The inflation data (change in the consumer prices index), the real interest rate (the money market rate using the consumer price index), the industrial production, the term structure, the GDP¹⁶ and consumption expenditures are all taken from the IMF's International Financial Statistics (IFS). The time series of domestic bank credit come from the European Central Bank (ECB) for the European countries. The source is the U.S. Federal Reserve for the United States. The consumer confidence indices are provided by the Economic European Commission for the countries of the European countries. The source is the University of Michigan Survey Research Center for the U.S. consumer confidence. All time series used are seasonally adjusted.

Annexe 2

The consumer confidence index is the result of a survey of a representative population of households. It reflects the perceptions and expectations of households both on their economic and financial situation as their propensity to spend and their views on the overall economic situation. The survey consists of simple questions with multiple choice answers are easily recognized. The relative score of each question is then calculated as the percent of favourable replies minus the percent of unfavorable replies, plus 100, rounded to the nearest whole number. The Michigan surveys are sent to households and the respondents are asked the following questions:

Q1. Do you think now is a good time for people to buy major household items?

- good time to buy
- uncertain
- depends
- bad time to buy

Q2. Would you say that you and your immediate family are better off or worse off financially than you were a year ago?

¹⁶ Quarterly data have been transformed into monthly data using moving averages.

- better
- same
- worse

Q3. Now turning to business conditions in the country as a whole-do you think that during the next twelve months the financial condition will be?

- good
- uncertain
- bad

Q4. Looking at the next five years, do you think we will continue having?

- good times
- uncertain
- bad times

Q5. A year from now, do you think your immediate family will be?

- better
- same
- worse

Table 1: Description of variables used in the study

Code	Variables	Measures	Sources
Macroeconomics variables			
INT	Real interest rate	Money market rate using consumer price index	International Financial Statistics
INF	Inflation	Change in the natural logarithm of the Consumer Price Index	International Financial Statistics
CREDIT/GDP	Domestic credit	Level of domestic credit divided by Gross Domestic Product	European central Bank & Federal reserve system
ST	Term spread	Difference between the yields on 10-year U.S. government bonds and 3-month Treasury bills	International Financial Statistics
IP	Industrial production	Change in the natural logarithm of industrial production index	International Financial Statistics
CD, CND et CS	Growth of durable goods, non-durables goods and services consumption expenditures	Change in the natural logarithm of durable goods, non-durables and services consumption expenditures	International Financial Statistics
Stock market variables			
P	Stock price index	Level of stock price index	Datastream
PER	Price Earning Ratio	Share price divided by earning per share	Bloomberg
DY	Dividend Yield	Cash dividend of the index divided by the value of the index	Bloomberg
RET	The year-one-year change in stock prices	Yearly change in stock prices	Datastream
Investor sentiment indicator			
SENT	Consumer sentiment index	The five questions making up the consumer sentiment index	Economic European Commission & University of Michigan Survey Research Center

Tableau 2: Characteristics of individual market crises

This table presents the characteristics of the stock market crises. The beginning of a crisis is the month when the index reaches its historical maximum over the 2-year window prior to the month when the crash is triggered. The beginning of the crash corresponds to the month when the CMAX intersects with a threshold. The date of trough is the month when the price index reaches its minimum. The date of recovery is the first month after the crash when the index reaches the pre-crash maximum. The magnitude of a crisis is the difference between the value of the index at its maximum and at its minimum. The length of the trough is the number of months between the date of the beginning of the crisis and the date of the trough. The length of the recovery period is the number of months for the index to return to the maximum. To avoid counting the same crisis more than once, a crisis is automatically eliminated if detected twice over a twelve month period.

				The duration of the crisis			Annual returns before crises		Annual returns after crises	
Beginning of crises	Beginning of crash	Date of trough	Date of recovery	Month to trough	Month to recovery	Price decline to trough	One year	Three years	One year	Three years
Belgium										
10/2000	09/2002	03/2003	05/2005	29	26	46.49%	0.793%	5.09%	20.45%	22.92%
05/2007	06/2008	03/2009	NA	13	NA	66.77%	27.80 %	53.94 %	NA	NA
Czech Republic										
05/1994	06 /1995	07/1995	03/2004	14	105	44.98%	NA	NA	54.96%	110.25%
11/2007	10/2008	03/2009	NA	11	NA	66.41%	24.03 %	109.26 %	NA	NA
Denmark										
10/2000	07/2002	02/2003	01/2005	28	23	43.83%	43.23%	59.76%	36.33%	63.48%
10/2007	09/2008	03/2009	NA	17	NA	57.77%	24.80%	49.48%	NA	NA
Germany										
02/2000	09/2001	09/2002	NA	31	NA	67.26%	55.09%	87.98%	NA	NA
10/2000	10/2002	03/2003	NA	17	NA	66.86%	22.72 %	84.73%	NA	NA
10/2007	10/2008	02/2009	NA	16	NA	54.48%	32.33%	76.25%	NA	NA
Ireland										
06/2001	06/2002	03/2003	12/2005	21	33	55.13%	21.24%	31.92%	29.87%	-44.02%
05/2007	07/2008	02/2009	NA	21	NA	62.17%	35.24%	87.67%	NA	NA
Greece										
11/1999	09/2001	09/2002	NA	22	NA	62.12%	98.27%	127.53%	NA	NA
04/2001	03/2003	03/2003	09/2005	23	30	55.35%	-32.64%	20.99%	16.23%	-15.53%
10/2007	10/2008	02/2009	NA	16	NA	71.20%	29.20%	114.30%	NA	NA
Spain										
02/2000	08/2001	07/2002	09/2006	29	50	33.88%	25.89%	137.22%	11.94%	-9.11%
09/2000	09/2002	09/2002	07/2005	24	34	50.39%	14.95%	50.62%	16.82%	17.45%
11/2007	10/2008	02/2009	NA	15	NA	51.64%	13.97%	81.29%	NA	NA

Tableau 2: Characteristics of individual market crises

This table presents the characteristics of the stock market crises. The beginning of a crisis is the month when the index reaches its historical maximum over the 2-year window prior to the month when the crash is triggered. The beginning of the crash corresponds to the month when the CMAX intersects with a threshold. The date of trough is the month when the price index reaches its minimum. The date of recovery is the first month after the crash when the index reaches the pre-crash maximum. The magnitude of a crisis is the difference between the value of the index at its maximum and at its minimum. The length of the trough is the number of months between the date of the beginning of the crisis and the date of the trough. The length of the recovery period is the number of months for the index to return to the maximum. To avoid counting the same crisis more than once, a crisis is automatically eliminated if detected twice over a twelve month period.

				The duration of the crisis			Annual returns before crises		Annual returns after crises	
Beginning of crises	Beginning of crash	Date of trough	Date of recovery	Month to trough	Month to recovery	Price decline to trough	One year	Three years	One year	Three years
France										
08/2000	09/2001	09/2002	NA	25	NA	38.43%	44.36%	139.14%	NA	NA
10/2000	10/2002	03/2003	NA	29	NA	50.76%	30.86%	133.55%	NA	NA
05/2007	10/2008	02/2009	NA	21	NA	55.72%	23.80%	66.33%	NA	NA
Italy										
08/2000	09/2001	09/2002	NA	25	NA	55.02%	42.66%	124%	NA	NA
10/2000	10/2002	03/2003	NA	29	NA	53.86%	44.27%	119.17%	NA	NA
05/2007	10/2008	02/2009	NA	21	NA	62.09%	18.71%	56.96%	NA	NA
Estonia										
08/1997	06/1998	12/1998	12/2004	16	72	81.59%	133.53%	NA	47.96%	41%
10/1997	07/1999	10/1999	03/2004	24	53	67.74%	152.22%	NA	79.76%	164%
01/2007	06/2008	02/2009	NA	25	NA	58.27%	52.85%	165.24%	NA	NA
Portugal										
02/2000	07/2001	07/2002	NA	29	NA	58.03%	30.23%	140.67%	NA	NA
08/2000	08/2002	03/2003	04/2007	31	65	55.80%	20.86%	59.80%	NA	NA
07/2007	10/2008	02/2009	NA	29	NA	55.30%	38.99%	88.50%	NA	NA
Slovenia										
06/1994	05/1996	07/1996	03/1998	25	20	41.67%	35.10%	NA	10.73%	6.10%
07/2007	02/2008	04/2008	NA	9	NA	30.96%	116.20%	145.16%	NA	NA
09/2007	03/2009	03/2009	NA	18	NA	70.08%	115.81%	149.90%	NA	NA
Finland										
04/2000	02/2001	09/2001	NA	17	NA	67.48%	165.15%	195.23%	NA	NA
06/2000	06/2002	07/2004	NA	49	NA	72.91%	103.58%	123.87%	NA	NA
10/2007	11/2008	02/2009	NA	16	NA	67.20%	44.54%	104.05%	NA	NA

Tableau 2: Characteristics of individual market crises

This table presents the characteristics of the stock market crises. The beginning of a crisis is the month when the index reaches its historical maximum over the 2-year window prior to the month when the crash is triggered. The beginning of the crash corresponds to the month when the CMAX intersects with a threshold. The date of trough is the month when the price index reaches its minimum. The date of recovery is the first month after the crash when the index reaches the pre-crash maximum. The magnitude of a crisis is the difference between the value of the index at its maximum and at its minimum. The length of the trough is the number of months between the date of the beginning of the crisis and the date of the trough. The length of the recovery period is the number of months for the index to return to the maximum. To avoid counting the same crisis more than once, a crisis is automatically eliminated if detected twice over a twelve month period.

				The duration of the crisis			Annual returns before crises		Annual returns after crises	
Beginning of crises	Beginning of crash	Date of trough	Date of recovery	Month to trough	Month to recovery	Price decline to trough	One year	Three years	One year	Three years
Sweden										
04/2000	08/2001	08/2002	NA	28	NA	63.21 %	84%	174.69%	NA	NA
09/2000	08/2002	03/2003	04/2007	30	49	60.94 %	46.35%	86.59%	NA	NA
05/2007	06/2008	01/2009	NA	20	NA	75.43 %	34.62%	86.16%	NA	NA
United Kingdom										
08/2000	09/2001	09/2002	10/2007	25	61	44.22 %	2.13%	29.70%	NA	NA
10/2000	10/2002	03/2003	07/2007	29	52	43.87 %	2.92%	32.96%	NA	NA
05/2007	09/2008	02/2009	NA	21	NA	41.96 %	15.68%	47.48%	NA	NA
United States										
07/2000	07/2001	06/2002	04/2007	23	58	39.99 %	14.94%	68.73%	-8.50%	NA
08/2000	08/2002	08/2002	12/2006	24	52	43.24 %	11.99%	51.64%	-22.46%	NA
09/2007	06/2008	02/2009	NA	17	NA	52.55 %	12.44%	37.08%	NA	NA

Table 4: Results of the Logit model estimation - stock market crises

This table presents the results of the Logit model. The dependent variable equals 1 for the 12 months preceding the crisis, and 0 during quiet periods. The 11 months following the crisis are excluded from the sample. The independent variables represent the real interest rate (INT), the year-one-year change in stock prices (RET), the Price Earnings Ratio (PER), the inflation (INF), the ratio domestic credit to GDP (CREDIT) and the investor sentiment ($SENT^{\perp}$). The statistics tabulated in parentheses correspond to the p-values. The sample period includes monthly data from April 1995 to June 2009. ***, **, * denote statistical significance at 1%, 5%, and 10%.

Explanatory Variables	Model 1	Model 2	Model 3
Constant	-1.234*** (-0.002)	-2.567*** (-0.000)	-2.276*** (-0.000)
INT	-0.112* (-0.07)		-0.089** (-0.041)
RET	-2.278** (-0.022)		-2.345** (-0.034)
PER	0.024* (0.079)		0.005 (0.265)
INF	-3.856** (-0.031)		-3.983** (-0.03)
CREDIT	0.877*** (0.006)		0.676*** (0.000)
$SENT^{\perp}$		0.157** (0.031)	0.134** (0.041)
R^2 McFadden LR stat	0.401 (0.000)	0.082 (0.000)	0.462 (0.000)
Forecast error (%)			
Seuil de 50 %			
Type A ⁽¹⁾	35.714	52.227	27.272
Type B ⁽²⁾	15.213	13.278	12.789
Seuil de 25 %			
Type A ⁽¹⁾	29.545	31.818	18.181
Type B ⁽²⁾	21.678	16.212	17.289

(1) Probability of crisis given no alarm.

(2) Percentage of false alarms.

Table 5: Cross sectional Logit model estimation results

This table presents the results of estimating the Logit model (3) where countries are pooled according to one of the determinants shown in the first column. The countries are allocated to one of two groups depending on whether they are above or below the median of a specific determinant. Sent denotes the coefficient estimated on the sentiment variable ($SENT^L$). $\Delta \text{adj.}R^2$ is the change in $\text{adj.}R^2$ when the sentiment indicator is included in the logit model (3). Types A and B errors are calculated for alert thresholds set at 25%. The sample period includes monthly data from April 1995 to June 2009. ***, **, * denote statistical significance at 1%, 5%, and 10%.

	Countries below median				Countries above median			
	Sent	$\Delta \text{adj.}R^2$	Type A	Type B	Sent	$\Delta \text{adj.}R^2$	Type A	Type B
<i>Cultural factors</i>								
Individualism	0.154**	0.067	0.136	0.117	0.08	0.009	0.340	0.245
Uncertainly avoidance	0.102*	0.019	0.272	0.324	0.143**	0.063	0.113	0.122
<i>Market integrity</i>								
Anti-director rights	0.123**	0.055	0.113	0.234	0.097	0.024	0.409	0.267
Corruption perception	0.165***	0.076	0.090	0.113	0.082	0.010	0.386	0.244
Accounting standards	0.119*	0.044	0.227	0.134	0.093	0.009	0.363	0.345

Table 6: Results of the Logit model estimation - stock market reversals points

This table presents the results of the Logit model. The dependent variable equals 1 for the 12 months preceding the crisis, and 0 during quiet periods. The 11 months following the crisis are excluded from the sample. The independent variables represent the real interest rate (INT), the year-one-year change in stock prices (RET), the Price Earnings Ratio (PER), the inflation (INF), the ratio domestic credit to GDP (CREDIT) and the investor sentiment ($SENT^{\perp}$). The statistics tabulated in parentheses correspond to the p-values. The sample period includes monthly data from April 1995 to June 2009. ***, **, * denote statistical significance at 1%, 5%, and 10%.

Explanatory Variables	Model 1	Model 2	Model 3
Constant	2.009*** (0.003)	0.895 (0.08)	1.878*** (0.000)
INT	0.223** (0.055)		0.211** (0.054)
RET	0.289* (0.078)		0.287** (0.088)
PER	0.376** (0.025)		0.099 (0.343)
INF	-0.021** (-0.045)		-0.020** (-0.048)
CREDIT	0.871*** (0.007)		0.814*** (0.000)
$SENT^{\perp}$		0.133* (0.067)	0.123* (0.086)
R² McFadden	0.123	0.021	0.142
LR stat	(0.003)	(0.015)	(0.005)
Forecast error (%)			
Seuil de 50 %			
Type A ⁽¹⁾	68.181	84.090	52.272
Type B ⁽²⁾	53.367	73.876	57.134
Seuil de 25 %			
Type A ⁽¹⁾	56.818	75.000	45.454
Type B ⁽²⁾	62.298	82.989	74.435

(1) Probability of crisis given no alarm

(2) Percentage of false alarms of total alarms